THE NORMALITY OF RETURNS DISTRIBUTIONS FOR BET AND S&P 500 INDEXES. A COMPARATIVE ANALYSIS

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Abstract

Currently, worldwide capital markets dispose of huge capitalizations, leading to extremely high investor exposure. At the same time, the turbulence currently occurring within the capital markets determines the existence of particularly high investment risks. Also, the high volatility of the periods characterized by economic instability determines pronounced asymmetries regarding the distributions of daily returns. The main methods of capital market risk estimation are based on the assumption of normality of daily returns distributions. But, in recent years, research has revealed that returns no longer display characteristics of normal distributions, being rather close to other families of distributions (asymmetric, exponential). The paper aims to test the normality of daily returns in the light of the latest developments within the capital market, currently dominated by unpredictable evolutions and a strong downward trend in the current economic context, caused by the Covid-19 pandemic. We also aim to build an indicator able to highlight those moments that are close to normality and efficiency, and afterwards, study whether or not the proposed indicator can be used as a predictor for extreme events.

Key-words: structural breaks, normality tests, Hurst exponent, normality – efficiency indicator, asymmetry

JEL Classification: C46, G14

This work was cofinanced from the European Social Fund through Operational Programme Human Capital 2014-2020, project number POCU/380/6/13/125015 ”Development of entrepreneurial skills for doctoral students and postdoctoral researchers in the field of economic sciences”.

Introduction

The multitude and magnitude of the financial crises of the last decades and the intensification of their contagion degree represent the very essence of risk manifestation, showing unequivocally that the risks undertaken by capital market investors are not negligible and become increasingly unpredictable.

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Capital market crises are no longer just a local phenomenon, they have also acquired a global character, due to the various contagion channels in the economy. Thus, the contagion phenomenon contributes to the transmission of financial crises, due to the high degree of interconnection – both of national economies in general and of capital markets in particular. In addition to the transmission and spread of economic crises, it has been often found that contagion channels even contribute to their increase.

Within the current context of economic reality, characterized by instability, volatility and contagion, the huge capitalization[*] of the stock markets determines an immense exposure of investments in this segment of the economy. During a stock market crisis, huge amounts of money can evaporate in minutes, or even seconds. Under these conditions, a correct estimation of stock market risk is a matter of great interest, a real challenge for the financial system, especially during periods of volatility or turbulence. Incorrect risk estimation leads to irrational exposure, which in turn can lead to major losses, which will eventually lead to market instability. Therefore, finding a robust method of risk estimation becomes a vital stage of the investment process within current capital markets, both for individual investors and especially for institutional investors.

Within the process of selecting and applying the most appropriate method of estimating the risks to which investors are exposed, it is often impossible to comply to the multiple theoretical assumptions on which these methods are based. One of the most important hypotheses, very common among risk estimation models, is the hypothesis that the financial assets return series follow normal distributions.

Periods of economic instability, such as the one we are currently going through, lead to increased volatility in capital markets. Some investors try to limit their exposure, while others try to exploit the moments with high volatility. Also, bad rumours and negative news (whether real or false) contribute, on the one hand, to an increase in volatility and, on the other hand, to the intensification of imitative behaviours, with an overwhelming impact on the allocation efficiency of the capital market. The high volatility presently exhibited by the capital markets and the presence of imitative mass behaviours generate strong asymmetries in the returns series. Thus, in recent years, several studies have emerged, contradicting the viability of the returns series normality hypothesis, arguing that a symmetrical distribution, such as the normal one, cannot accurately describe the current developments of the financial assets returns series, characterized by strong asymmetries.

Under these circumstances, we considered it appropriate to analyse the changes that occur within the normality characteristics of the returns series distributions, when the market switches from normal operating conditions to turbulent periods. From a statistical point of view, successive rapid alternations of relative calm and turbulence should be characterized by strong asymmetries of the returns series. For such distributions, variance and semi-variance models become irrelevant. Such methodological issues influence the accuracy of risk estimation models, dramatically affecting the provided results. In this respect, the study seeks to determine whether, in reality, in times of stock market crisis, there are significant differences from periods of normal operation, in terms of the normality of returns series distributions.

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[*] New York Stock Exchange Stock Market Capitalization in 2018 was about US$ 23 trillion, while the US GDP of the same year was only US$ 20,5 trillion.

Thus, the first objective of our research was to determine whether the returns display normal distribution characteristics, both in normal operating conditions and in periods of high volatility, such as the last 3 months.

The second research objective focused on determining the extent to which the characteristics of the distributions remain unchanged or change from periods of normal operation to those characterized by volatility and turbulence.

Another objective pursued within the study was to build an indicator able to capture normality, but also the random nature of the analysed time series (randomness being considered a measure of informational efficiency).

Finally, the fourth objective of our study was to verify whether the structural breaks in the evolution of this indicator are consistent with certain major changes in asset returns or with certain moments associated with various noticeable events.

1. Literature review

Periods of economic or social turmoil are always best reflected in the functioning of capital markets. This idea is demonstrated by a study conducted in 2015 (Ioan, 2015), which revealed the existence of a certain connection (Pirtea et al., 2009) between the cyclical component of Gross Domestic Product and the cyclical component of the main stock market index. Thus, the paper demonstrated that any shock in the time series variance of one of the cyclical components (GDP or market index) will cause an appropriate correction within the variance of the other time series, so that a combination of the two variances would remain within a certain confidence interval. In economic terms, such a connection is interpreted by successive adaptations and adjustments made by both of the analysed time series – GDP and stock market index, while the analysed time series are continuously influenced by each other.

Having more and more papers demonstrating that the normality of returns is an increasingly rare concept in reality, it becomes obvious that especially in periods of economic instability, the financial assets returns distributions will be furtherly away from the Gaussian curve.

McCauley (2007) discusses the widening deviation of these distributions from the normal curve, recalling works from the '60s (M. F. M. Osborne or Bachelier) that tried to fit the empirical distributions in order to demonstrate their deviations from the normal distribution. McCauley questions, just like Mantegna and Stanley, (2000) the existence of strongly asymmetric probability densities. Han's work (2013) demonstrates the existence of a strong connection between the performance of financial assets on the one hand and the mean and asymmetry of historical distributions, on the other hand, confirming, at the same time, the existence of the fat tails effect.

In Sheikh and Qiao' paper (2009), the authors show that due to the absence of normality in the series of returns, extreme negative events are observed with a much higher frequency than allowed by the currently used risk estimation models. Consequently, traditional allocation models, based on normal distributions, tend to underestimate the risk of the constructed portfolios. The situation described in their paper is common among so-called traditional risk estimation models, as many of them are based on the assumption of normality[†].

In all these situations, it is important to adopt flexible statistical models, able to cope with abnormal asymmetries and kurtoses cases and, at the same time, to allow a continuous alternation from non-normality to normality (Huber, 1981; Azzalini, 1986; Hampel et al., 1986). Such characteristics are captured by the family of Asymmetric Exponential Power Distributions (Ayebo, 2003).

Cont (2001), referring to the well-known *stylized facts*, states that the series of returns obtained on the capital market have the following characteristics:

- Heavy tails: returns distributions tend to display asymmetries, elongations such as power functions. Even the series from which the volatility component was removed maintain these asymmetries;
- Asymmetry between gain and loss: stock price declines are higher than price increases.

However, Cont states that the capital market data series show *aggregational Gaussianity*, i.e. by increasing the time horizon of the analysis, the obtained returns time series will, however, display normal distributions.

Among the econo – physics researches, Didier Sornette (2002, 2004) observes an extremely high similarity between the evolution of stock market prices, especially stock market indices and the evolution of a log-periodical function, in the periods preceding the stock market crashes. These situations present a price formation process that is no longer a *random walk*. Sornette states that any price evolution deviation from a random walk evolution (which actually describes an ordinary day) derives from the behaviour and actions of the market participants. The hypothesis approached by econo – physicists, states that the formation of the premises that lead to stock market crashes occurs with the creation of strong correlations within the market, which contributes to the emergence of cooperative behaviours of market participants (imitative mass behaviours, herding behaviours). Within a certain period of time, all this will lead towards the stock market crash.

The importance of an in-depth analysis regarding the empirical distributions of the studied data emerges from all the above, in order to be able to decide on a proper and pertinent choice of risk estimation method. Also, studying the theory of econo - physicists, especially the one proposed by Sornette, we notice the importance of a separate study of the periods of calm, when the market functioning stays in normal parameters and of those periods characterized by turbulence or even crises.

2. Methodology and data

In order to conduct our study, we chose the current period, dominated worldwide by the onset of an economic crisis generated by the general stagnation of economic activity, within the context of limiting the spread of Covid-19 disease. In this conditions, we performed a comparative analysis, from two points of view:

[†] e. g. Markowitz model, Sharpe model, delta normal Value at Risk or Geometric Brownian Motion (the base of Black Scholes model)

- From the *spatiality* point of view, we chose the main market index of the United States of America, S&P 500, considered by specialists as a true benchmark of the global evolution of stock exchanges. On the other hand, we chose the main market index in Romania, the BET index, as the representative of the capital market of an emerging economy;
- From the analysis *period* point of view, we performed a comparative analysis between the period of relative calm, prior to the outbreak of the Covid-19 pandemic, the period marked by the onset and spread of the pandemic and the period marked by its global settling and the establishment of the emergency state in several countries. Thus, we analysed five different periods:

- Third quarter of 2019;
- Fourth quarter of 2019;
- Entire year 2019; The first three sub periods were chosen in order to test, on various time frames, the behaviour of the returns series during periods of calm and normal functioning of the capital market;
- First quarter of 2020, the period marked by the outbreak and the increase of the pandemic;
- 01.01.2020 - 05.05.2020, a period that includes both the outbreak of the pandemic inside the USA and Romania, but also the establishment of the state of emergency and a major stagnation of the economy, imposed by quarantine / isolation measures.

We used daily data, obtained from Yahoo Finance (S&P 500) and from www.tradeville.ro (BET index). The normality analysis of the returns series of BET and S&P500 indices was performed, using the classical normality tests:

- Shapiro – Wilk test;
- Anderson – Darling test;
- Kolmogorov – Smirnov test;
- Jarque – Bera test;
- Anscombe – Glynn test;
- Bonett – Seier test;
- Geary test;
- The skewness and kurtosis values of the analysed empirical distributions.

Following the normality analysis of the returns distributions for the two market indices, we built an normality and randomness indicator (which actually shows the level of informational efficiency of the market), using a 30-day mobile window:

$$I = S^2 + (K - 3)^2 + (H - 0{,}5)^2 \qquad (1)$$

where:
S = Pearson skewness of the returns series (0 for a normal distribution);
K = Pearson kurtosis of the returns series (3 for a normal distribution);
H = Hurst exponent of the returns series (a value of 0.5 indicates an uncorrelated, random distribution);

Afterwards, based on the constructed indicator, we determined, using the Bai – Perron test, the moments of structural breaks.

All analyses and tests were performed using R software.

3. Main results

After performing the mentioned normality tests (at a probability of 0.95), we conclude that for most of the analysed periods (except for the BET index in the fourth quarter of 2019), the normality hypothesis is not confirmed (tables 1 – 5), the values of skewness and kurtosis are very far from those specific for the normal distribution, *p-value* for the Shapiro – Wilk test is very small, etc. In the fourth quarter of 2019, the daily returns of BET index show characteristics of a normal distribution, confirmed by most of the performed tests (Shapiro – Wilk providing the most accurate results, usually). During the same period, it can be seen that the values provided by these tests for S&P500 are quite close to those specific for a normal distribution (Shapiro – Wilk confirming normality at a confidence level of 0.9). The proximity of a Gaussian distribution is also confirmed by the drastic decrease of the Jarque – Bera statistic for this period or by the increase of the *p-value* of the Kolmogorov – Smirnov test.

Taking into account the results presented below, the research tends to confirm the results discussed in the literature review section, which argue that currently, Gaussian distributions of returns series are particularly difficult to find in the case of empirical distributions.

Table 1. Results of normality tests for third quarter 2019

Index	Test	Third quarter 2019		
BET	Shapiro-Wilk	W = 0.93484	p-value = 0.001824	
	Anderson-Darling	A = 1.0712	p-value = 0.007653	
	Kolmogorov-Smirnov	D = 0.10773	p-value = 0.4278	
	Jarque-Bera	JB = 26.204	p-value = 2.042e-06	
	Anscombe-Glynn	kurt = 5.510061	z = 2.8589	p-value = 0.004251
	Bonett-Seier	tau = 0.0047921	z = 2.5359128	p-value = 0.01122
	Geary	0.7351743		
	Kurtosis	5.510061		
	Skewness	0.8983524		
S&P500	Shapiro-Wilk	W = 0.92116	p-value = 0.0006182	
	Anderson-Darling	A = 1.0756	p-value = 0.007437	
	Kolmogorov-Smirnov	D = 0.090143	p-value = 0.652	
	Jarque-Bera	JB = 24.808	p-value = 4.101e-06	
	Anscombe-Glynn	kurt = 5.256683	z = 2.6817	p-value = 0.007324
	Bonett-Seier	tau = 0.0066835	z = 3.3537974	p-value = 0.0007971
	Geary	0.7142385		
	Kurtosis	5.256683		
	Skewness	-1.043812		

Source: own calculations in R

Table 2. Results of normality tests for fourth quarter 2019

Index	Test	Fourt quarter 2019		
BET	Shapiro-Wilk	W = 0.97224	p-value = 0.1581	
	Anderson-Darling	A = 0.45988	p-value = 0.2533	
	Kolmogorov-Smirnov	D = 0.086255	p-value = 0.7277	
	Jarque-Bera	JB = 4.5739	p-value = 0.1016	
	Anscombe-Glynn	kurt = 3.87471	z = 1.5929	p-value = 0.1112
	Bonett-Seier	tau = 0.0036268	z = 1.8839995	p-value = 0.05957
	Geary	0.7501328		
	Kurtosis	3.87471		
	Skewness	-0.4873654		
S&P500	Shapiro-Wilk	W = 0.95429	p-value = 0.02009	
	Anderson-Darling	A = 0.55259	p-value = 0.1483	
	Kolmogorov-Smirnov	D = 0.079933	p-value = 0.7858	
	Jarque-Bera	JB = 15.602	p-value = 0.0004094	
	Anscombe-Glynn	kurt = 4.861768	z = 2.4276	p-value = 0.0152
	Bonett-Seier	tau = 0.00422	z = 2.12271	p-value = 0.03378
	Geary	0.7438877		
	Kurtosis	4.861768		
	Skewness	-0.7869854		

Source: own calculations in R

Table 3. Results of normality tests for 2019

Index	Test	2019		
BET	Shapiro-Wilk	W = 0.92961	p-value = 4.831e-10	
	Anderson-Darling	A = 4.678	p-value = 1.284e-11	
	Kolmogorov-Smirnov	D = 0.090589	p-value = 0.02341	
	Jarque-Bera	JB = 267.46	p-value < 2.2e-16	
	Anscombe-Glynn	kurt = 7.862321	z = 6.0657	p-value = 1.314e-09
	Bonett-Seier	tau = 0.0056172	z = 10.0221595	p-value = 2.2e-16
	Geary	0.6788856		
	Kurtosis	7.862321		
	Skewness	-0.1052742		
S&P500	Shapiro-Wilk	W = 0.94326	p-value = 2.771e-08	
	Anderson-Darling	A = 2.8901	p-value = 2.769e-07	
	Kolmogorov-Smirnov	D = 0.089311	p-value = 0.03648	
	Jarque-Bera	JB = 125.76	p-value < 2.2e-16	
	Anscombe-Glynn	kurt = 6.225749	z = 4.9418	p-value = 7.741e-07
	Bonett-Seier	tau = 0.0055885	z = 6.9461569	p-value = 3.754e-12
	Geary	0.7103085		
	Kurtosis	6.225749		
	Skewness	-0.6362033		

Source: own calculations in R

Table 4. Results of normality tests for first quarter 2020

Index	Test	Trimestrul întâi 2020		
BET	Shapiro-Wilk	W = 0.84022	p-value = 5.262e-07	
	Anderson-Darling	A = 4.076	p-value = 2.986e-10	
	Kolmogorov-Smirnov	D = 0.20327	p-value = 0.007878	
	Jarque-Bera	JB = 71.888	p-value = 2.22e-16	
	Anscombe-Glynn	kurt = 7.585069	z = 3.7594	p-value = 0.0001703
	Bonett-Seier	tau = 0.014754	z = 8.153123	p-value = 3.546e-16
	Geary	0.6143582		
	Kurtosis	7.585069		
	Skewness	-1.087215		
S&P500	Shapiro-Wilk	W = 0.91447	p-value = 0.0002943	
	Anderson-Darling	A = 2.2632	p-value = 8.394e-06	
	Kolmogorov-Smirnov	D = 0.17605	p-value = 0.03316	
	Jarque-Bera	JB = 17.304	p-value = 0.0001748	
	Anscombe-Glynn	kurt = 5.430291	z = 2.7933	p-value = 0.005217
	Bonett-Seier	tau = 0.023693	z = 5.768832	p-value = 7.982e-09
	Geary	0.6604206		
	Kurtosis	5.430291		
	Skewness	-0.3816135		

Source: own calculations in R

Table 5. Results of normality tests for 01.01.2020 – 05.05.2020

Index	Test	2020, 01.01.2020 - 05.05.2020		
BET	Shapiro-Wilk	W = 0.8817	p-value = 1.077e-06	
	Anderson-Darling	A = 3.6373	p-value = 3.723e-09	
	Kolmogorov-Smirnov	D = 0.18724	p-value = 0.004811	
	Jarque-Bera	JB = 76.179	p-value < 2.2e-16	
	Anscombe-Glynn	kurt = 7.103606	z = 3.8320	p-value = 0.0001271
	Bonett-Seier	tau = 0.014956	z = 7.942313	p-value = 1.984e-15
	Geary	0.6368297		
	Kurtosis	7.103606		
	Skewness	-1.051156		
S&P500	Shapiro-Wilk	W = 0.93022	p-value = 0.00019	
	Anderson-Darling	A = 2.0826	p-value = 2.437e-05	
	Kolmogorov-Smirnov	D = 0.12687	p-value = 0.1187	
	Jarque-Bera	JB = 29.772	p-value = 3.429e-07	
	Anscombe-Glynn	kurt = 5.764325	z = 3.1968	p-value = 0.00139
	Bonett-Seier	tau = 0.022402	z = 6.248629	p-value = 4.141e-10
	Geary	0.6675251		
	Kurtosis	5.764325		
	Skewness	-0.4372211		

Source: own calculations in R

The above tables show that the normality tests results invalidate the presence of normality in most of the analysed cases, when the tests are applied in a ***static manner***, at a certain time, for a whole period of time. By calculating the proposed indicator, a normality and randomness indicator will be obtained, this time in a ***dynamic manner***, due to the construction of this indicator on a 30-day mobile window.

The following results prove that although the initial results deny the presence of normality characteristics in a static analysis, at some point, normality still occurs, but it is not maintained in a continuous or long-term manner. (figures 1 – 5).

Figure 1. The evolution of the proposed indicator in the third quarter of 2019
Source: own processing

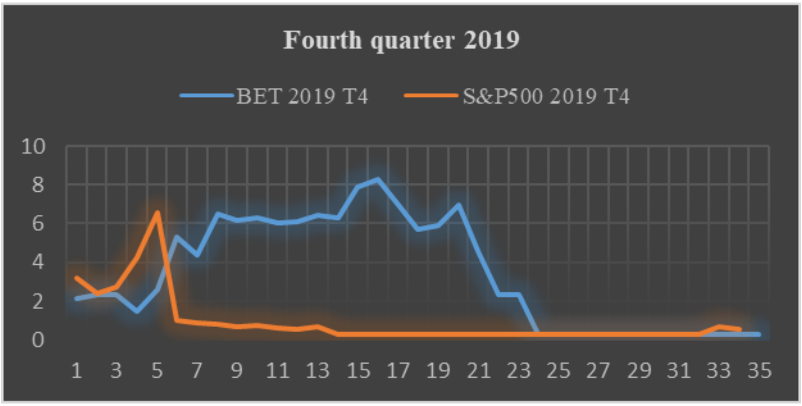

Figure 2. The evolution of the proposed indicator in the fourth quarter of 2019
Source: own processing

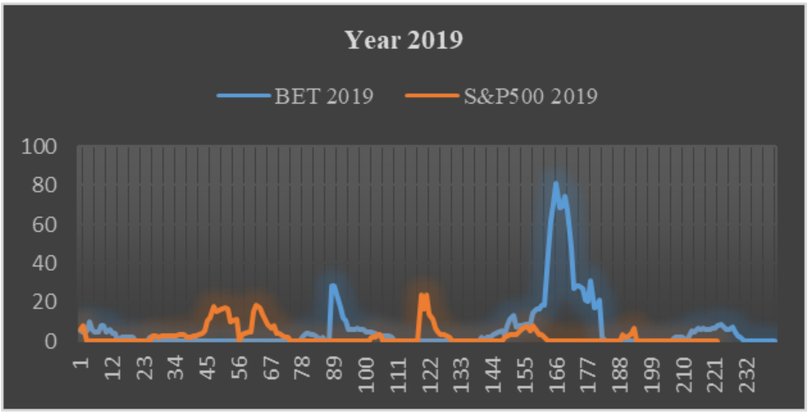

Figure 3. The evolution of the proposed indicator in 2019
Source: own processing

Figure 4. The evolution of the proposed indicator in the first quarter of 2020
Source: own processing

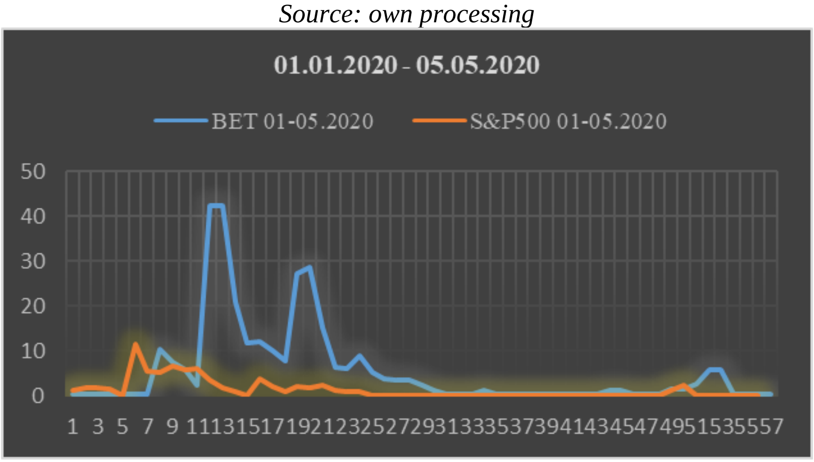

Figure 5. The evolution of the proposed indicator in 01.01.2020 – 05.05.2020

Source: own processing

Analysing the figures above, we can see that there are several times when the value of the proposed indicator approaches and even remains for a certain period around zero. We can also see that in the case of S&P500, the value of the indicator is close to zero more often than in the case of BET. Thus, we can conclude that the returns distribution of S&P500 is closer to a Gaussian distribution. It should also be noted that while the time series of skewness and kurtosis display major fluctuations, the time series obtained for the Hurst exponent remain most of the time close to 0.99.

The indicator computed for the returns of S&P500 displays fewer major fluctuations, fewer shocks than the indicator computed for the returns of BET, which has a much more fluctuating and volatile evolution.

These evolutions characterized by high volatility, observed in the evolution of the constructed indicator, raised questions about the moments of shocks. Thus, we also performed a structural breaks test for the data series of the constructed indicators, using the Bai – Perron test. The results of this test are presented in Annex 1.

Afterwards, we analysed the evolution of S&P500 and BET at the exact times indicated by the Bai – Perron test as days with structural breaks. For 2019, the analysis revealed a single day, in the case of BET, with a volatility level higher than that of the adjacent days, i. e. the day of 27.08.2019, characterized by a return of 2.37%. For the rest of the days indicated by the Bai – Perron test as structural break days, the return of that day does not confirm any particular event, so the built-in indicator provides a series of false alarms.

Within the analysis carried out for the first quarter of 2020, the structural break days indicated by the Bai – Perron test correspond to the following movements of the BET Index close price:

- Day 7 is prior to 24.02.2020, which has a decrease of 2.46%;
- Day 11 shows a decrease of 1.47% and is to 28.02.2020, which shows a decrease of 4.62%;
- Day 14 displays an increase of the index of 3.63% and is prior to 03.03.2020, which shows an increase of 2.54%;
- Days 17, 18 and 19 show variations of -1.77%, -1.55%, -7.53%, respectively;
- Day is 12.03.2020, showing a decrease of 5.15%;
- Day 24 is 16.03.2020, with a decrease of 9.58%;
- Day 25 has an increase of the index of 6.11% and is the one prior to 18.03.2020, which has a decrease of the BET index of 3.56%;
- Days 30, 31 and 33 show variations of 6.15%, 1.99%, -1.23%, respectively;

For S&P500, in the first quarter of 2020, the structural break days indicated by the Bai – Perron test correspond to the following price movements:

- Day 5 shows a decrease of the index of 1.05% and is the one before 24.02.2020, which shows a decrease of 3.35%;
- Day 7 is 25.02.2020, with a decrease of 3.03%;
- Day 11 displays an increase of the index of 4.60% and is the one prior to 03.03.2020, with a decrease of 2.81%;

- Day 17 shows an increase of the index of 4.94% and is the one prior to 11.03.2020, which shows a decrease of 4.89%;
- Day 21 is 16.03.2020 and shows the largest decrease of S&P500 since the beginning of the analysed period (01.01.2019), of 11.98%;
- Day 23 is 18.03.2020, with a decrease of 5.18%;
- Day 26 is 23.03.2020, and has a decrease of 2.93%;
- Day 29 is March 26, 2020 and shows an increase of 6.24%.

If we extend the analysis period until 05.05.2020, the structural break days indicated by the Bai – Perron test, in the case of BET are:

- Day 8 is 24.02.2020, having a decrease of 2.46%;
- Day 15 is 03.03.2020, with an increase of 2.54%;
- Day 17 is 05.03.2020, and shows a decrease of 1.77%;
- Day 18 is 06.03.2020, and shows a decrease of 1.55%, being the day before 09.03.2020, which shows one of the most drastic decreases in 2020, of 7.53%;
- Day 21 is 09.03.2020, and shows a decrease of 3.91%, being the day before 10.03.2020, with a decrease of 5.15%;
- Day 23 is prior to 16.03.2020, and shows the largest decrease in 2020, of 9.58%;
- Day 26 is 18.03.2020, and shows a decrease of 3.56%, being the day before day 27, 19.03.2020, which shows an increase of 1.26%;
- Day 31 is 25.03.2020, showing an increase of 1.99%;
- Day 33 is March 27, 2020, and shows a decrease of 1.23%;
- Day 36 is 01.04.2020, with a decrease of 2.62%, being the day before day 37, 02.04.2020, which shows an increase of 1.66%;
- Day 39 is 06.04.2020, and shows an increase of 2.4%, being the day before 07.04.2020, which has an increase of 4.07%;
- Day 46 is 15.04.2020, having decrease of 4%;

For the same analysis period (until 05.05.2020), the structural break days indicated by the Bai – Perron test, in the case of S&P500 are:

- Day 8 is 26.02.2020, being the day before 27.02.2020, which shows a decrease of 4.42%;
- Day 10 is 28.02.2020, the day before 02.03.2020, with an increase of 4.6%;
- Day 13 is 04.03.2020, with an increase of 4.22%, being the day before 05.03.2020, which displays a decrease of 3.39%;
- Day 17 is 10.03.2020, with an increase of 4.94%. The following days bring successive decreases of 4.89% and 9.51%. Then the next day shows an increase of 9.29%. Then, on the 21st, the biggest decrease of 2020 of 11.98% appears;
- Day 26, 23.03.2020, shows a decrease of 2.93%, being the day before 24.03.2020, which shows an increase of 9.38% (day 27);
- Day 32, 31.03.2020, has a decrease of 1.6%, being the day before 01.04.2020, with a decrease of 4.41%;
- Day 35, 03.04.2020, shows a decrease of 1.51%, being the day before 06.04.2020, which shows an increase of 7.03% (day 36);
- Day 41, 14.04.2020, shows an increase of 3.06%, being prior to 15.04.2020, with a decrease of 2.2%;

- Day 45, 20.04.2020, shows a decrease of 1.79%, being the day before 21.03.2020, with a decrease of 3.07% (day 46);

It is thus revealed that the constructed indicator is able to capture the days with the highest turbulence and volatility.

Conclusions

The normality analysis of the daily returns series is important in the first place as a premise for the risk estimation models, but also in terms of ensuring the analyst / investor of the possibility that efficiency and atomicity exist on the capital market.

Regarding the analysis of normality (both statically and dynamically), the obtained results revealed some important aspects:

1. The normality of the daily returns series appears within a single time period, leaving room for other distributions for relatively long periods of time;

2. Normality does not appear especially in periods of calm, compared to those characterized by turbulence;

3. Normality is not a precondition for a stock market crash, nor a guarantee that a crash will not occur on the next day / period.

Since the premise of normality is not respected, the "classical" methods of risk estimation cannot be effective, therefore investors who use models dependent on this premise have been extremely exposed to risks during this turbulent period and have probably suffered significant losses.

The importance of the approach is even higher as the current crisis of the capital markets has a completely different nature in comparison with the previous major crises (1987 crash, dot.com crash in the early 2000s, real estate crisis that started in 2006 – 2007 in the USA, etc.). All the above were crises that made a major correction at a macroeconomic level, often through the capital market. This time, we analyse a capital market crisis, caused by an extreme social phenomenon, which will have delayed side effects on the economy, through a *spillover effect*, an idea also sustained by other researchers (Goodell, 2020). This social crisis will not cause a correction decrease on the capital market, like the ones described by the above mentioned crises, but rather a decrease caused by fear, panic, the prospect of a future contraction of economic activity, as a consequence of extreme phenomena such as pandemics, wars, earthquakes, etc. Especially because of the nature of the current crisis, it is certain that the market is decreasing and will continue to decline, which will lead to strong asymmetries in the daily returns series. This fact is also revealed by the increasingly obvious absence of normality in the returns series, an idea demonstrated by the present paper. The bad news coming from the economy and from the health system will continue to create panic, herding behaviours and will increase the downward trend. Returns will no longer have normal distributions and "classic" risk estimation models will provide increasingly erroneous results. It becomes clear that from now on, investors will have to use only risk estimation models that do not contain the premise of normality of daily returns series. The normality of the returns series can no longer be used as a premise, so the paper proposes to exploit the utility of the lack of normality. In these conditions, this paper proposes an Indicator that exploits the moments of "extreme bias" from normality, the structural breaks in normality, in order to provide the investor with a certain amount of time to be able to prevent the effects of large market movements, and the results are quite promising.

The evolution of BET returns shows a greater distancing from the characteristics of normality and efficiency, which may mean that often trading is rather based on rumours and imitative behaviour than on technical or fundamental analysis principles.

The periodic absence of normality implies the impossibility of using certain risk estimation models as well as certain price formation models.

Analysing the Hurst exponent results (calculated on a 30-day moving window), we will find values of 0.99 in most cases, indicating persistent time series, with solid tendencies to maintain a certain trend of evolution, thus revealing the lack of informational efficiency.

The Bai – Perron test indicates certain structural breaks in the proposed Indicator, which, in most days of 2019, offers false alarms, as it indicates days with normal trading, without large variations in closing prices and low volatility. But, in fact, 2019 didn't really have a very volatile evolution, both indices displaying an upward trend, with a moderate slope.

There are better results in 2020, for both indices, in an extremely volatile period, governed by large fluctuations and significant declines in closing prices. During this period, (the first part of 2020), in several occasions, the structural breaks in the evolution of the proposed Indicator, appear the day before certain "big" events, which makes the indicator useful for out of sample analysis.

In the current economic and social context, there are authors (Zhang et al., 2020) who advocate for countries, especially those radically affected by the pandemic, to implement investor protection measures. In this respect, the results obtained in this paper could suggest the validity of some opinions that support the implementation of daily volatility limitations by capital market supervisors (in the sense of trading suspension of financial assets whose prices reach the required threshold), considering that this measure would protect investors from major declines that occur suddenly in a single day, providing them with a certain reaction time[‡]. However, there are also opinions stating that this type of measure would be a form of capital control or a measure that would drastically reduce market liquidity.

Bibliography

[1] Ayebo, A. and T. J. Kozubowski, (2003), An asymmetric generalization of Gaussian and Laplace laws, *Journal of Probability and Statistical Science*

[2] Azzalini, A., (1986), Further results on a class of distributions which includes the normal ones, *Statistica* 12, pp. 171–178

[3] Bottazzi, G. and A. Secchi, (2011), *A New Class of Asymmetric Exponential Power Densities with Applications to Economics and Finance. Industrial and Corporate Change*, Oxford University Press (OUP), pp. 991

[4] Cont, R., (2001), *Empirical properties of asset returns: stylized facts and statistical issues*, Quantitative Finance, Institute of Physics Publishing, Volume 1, pp. 223 – 236

[‡] This type of measure has already been imposed by some of the largest stock exchanges in the world, e. g. CME Group;

[5] Goodell, J.W., (2020), *COVID-19 and finance: Agendas for future research*, Finance Research Letters, April 2020
[6] Hampel, F., E. Rocchetti, P. Rousseeuw, and W. Stahel (1986), *Robust Statistics: The Approach Based on the Influence Functions*, New York: John Wiley and Sons
[7] Han, L., (2013), *Empirical study on stock's capital returns distribution and future performance*, TigerPrints, 5-2013, Clemson University
[8] Huber, P. (1981), *Robust Statistics*, New York: John Wiley and Sons.
[9] Ioan, R., (2015), The Co-Movement Connection Between The GDP and The Main Stock Market Index. The Cases of USA and Romania, *Annals of the „Constantin Brâncuşi" University of Târgu Jiu*, Economy Series, Issue 6/2015, pp. 186 – 192
[10] Kozubowski, T. J. și K. Podgorski, (2001), Asymmetric Laplace Laws and Modeling Financial Data, *Mathematical and Computer Modelling*, 34, pp. 1003-1021
[11] Mantegna, R. and H. Stanley, (2000), *An Introduction to Econophysics: Correlations and Complexity in Finance*, Cambridge University Press
[12] McCauley, J. (2007), *Dynamics of Markets: Econophysics and Finance*, Cambridge University Press
[13] Pirtea, M.G., R. Ioan, B. Dima and Șt.M. Cristea, (2009), *The "Co-Movement" Connection between Two Time Series*, The 3rd European DAAAM International Young Researchers' and Scientists' Conference, Vienna, Austria
[14] Sheikh, A. Z. and H. Qiao, (2009), Non-normality of market returns. A framework for asset allocation decision-making, *J. P. Morgan Asset Management*
[15] Sornette, D., (2002), *Critical Market Crashes*, part of "Why stock market crash", Princeton University Press, January 2003; http://www2.math.uu.se/cim/seminars/CriticalMarketCrashes.pdf,
[16] Sornette, D. and W. X. Zhou, (2004), Predictability of large future changes in major financial indices, *International Journal of Forecasting*, Volume 22, No. 1, January – March, pp. 153-168
[17] Zhang, D. M. Hu and Q. Jib, (2020), Financial markets under the global pandemic of COVID-19, Finance Research Letters, April 2020

Annex 1. Results of Bai – Perron test (using R)

BET 2019, third quarter
```
Breakpoints at observation number:
m = 1          18
m = 2     12       24
m = 3      9     18 27
m = 4   7    14 21    29
m = 5   6 12    18 24 30
m = 6   5 10 15 20 25 31
Fit:
m   0      1      2      3      4      5      6
RSS 4218.0 1054.5  468.0  262.5  168.0  115.5   85.0
BIC  287.5  243.4  220.6  206.4  197.1  190.5  186.3
```

BET 2019, fourth quarter
```
Breakpoints at observation number:
m = 1        17
m = 2     11    23
m = 3   8    17 26
m = 4   7 14    21 28
m = 5   5 11 17 23 29
Fit:
m   0      1      2      3      4      5
RSS 3570.0  892.5  396.0  222.0  140.0   97.5
BIC  268.3  226.9  205.6  192.4  183.4  177.8
```

BET 2019
```
Breakpoints at observation number:
m = 1         121
m = 2      80      161
m = 3   60     120      181
m = 4   48 96      144 193
m = 5   40 80 120 160 201
Fit:
m   0       1       2       3       4       5
RSS 1181021  295240  131220   73810   47236   32800
BIC    2753    2429    2243    2115    2018    1941
```

BET 2020, first quarter
```
Breakpoints at observation number:
m = 1        19
m = 2     12    25
m = 3      9  18    28
m = 4   7 14    22 30
m = 5   6 12 18 24    31
m = 6   5 11 17 22 28 33
Fit:
m   0      1      2      3      4      5      6
RSS 4569.5 1140.0  507.0  285.0  182.0  126.0   92.5
BIC  297.1  251.6  228.1  213.5  203.7  197.0  192.6
```

BET 2020, 01.01.2020 – 05.05.2020
```
Breakpoints at observation number:
m = 1         27
m = 2      18       37
m = 3      13 27    41
m = 4   10     21 33    44
m = 5   8  17 26    36 46
m = 6   7  15 23 31 39 47
Fit:
m   0       1       2       3       4       5       6
RSS 15428.0  3857.0  1710.0   962.5   616.0   427.5   312.0
```

```
BIC   489.1   418.2   379.9   355.2   337.9   325.1   315.3
```

S&P500 2019, third quarter

```
Breakpoints at observation number:
m = 1         17
m = 2      11    22
m = 3   8    16 25
m = 4   6 13    20 27
m = 5   5 11 17 22 28
Fit:
m   0      1      2      3      4      5
RSS 3272.5  816.0  363.0  204.0  129.5   90.0
BIC  258.8  218.6  198.2  185.6  177.2  171.9
```

S&P500 2019, fourth quarter

```
Breakpoints at observation number:
m = 1         17
m = 2      11    22
m = 3   8    16 25
m = 4   6 13    20 27
m = 5   5 11 17 22 28
Fit:
m   0      1      2      3      4      5
RSS 3272.5  816.0  363.0  204.0  129.5   90.0
BIC  258.8  218.6  198.2  185.6  177.2  171.9
```

S&P500 2019

```
Breakpoints at observation number:
m = 1          121
m = 2       80     161
m = 3   60     120     181
m = 4   48 96      144 193
m = 5   40 80 120 160 201
Fit:
m   0       1       2       3       4       5
RSS 1181021  295240  131220   73810   47236   32800
BIC    2753    2429    2243    2115    2018    1941
```

S&P500 2020, first quarter

```
Breakpoints at observation number:
m = 1         17
m = 2      11    23
m = 3   8    17 26
m = 4   7 14    21 28
m = 5   5 11 17 23 29
Fit:
m   0      1      2      3      4      5
RSS 3570.0  892.5  396.0  222.0  140.0   97.5
BIC  268.3  226.9  205.6  192.4  183.4  177.8
```

S&P500 2020, 01.01.2020 – 05.05.2020

```
Breakpoints at observation number:
m = 1          27
m = 2       17    36
m = 3       13 27    41
m = 4   10 21    32 43
m = 5   8  17 26 35 45
Fit:
m   0       1       2       3       4       5
RSS 14630.0  3654.0  1624.5   910.0   583.0   405.0
BIC   478.6   409.0   371.7   347.3   330.4   318.0
```